International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(10s) 2026 pp. 849-866
https://doi.org/10.70917/ijcisim-2026-3680
Article

Bridging Campus and Corporate: A Study of AI Readiness Among Job-Market-Ready Talents in Kerala

Geo P P[1], Kuldip Singh[2]

[1*]Management
[2] Desh Bhagat University, Mandi Gobindgarh, Distt. Fatehgarh Sahib, Panjab, India
Corresponding Email: geopp26@gmail.com

Abstract: As scaling AI becomes deeply intertwined with the modern business sector, checking if young fresh talents are competent to work with such technology has become very important and still very timely. This research explores the AI preparedness of young fresh talent who are just started their job or in search and who are preparing to hit the job market from institutes in Kerala, concentrating on their acceptance and capability to change in the situations where the AI Tools will be integral part of work force in future. The current research is founded on Technology Acceptance Model (TAM) and explores the significance of Perceived Ease of Use (PEU) and Perceived Usefulness (PU) in young fresh talents formation of opinions about AI. The researcher adopts a quantitative approach; with descriptive and exploratory lens. The researcher collected data from a randomly selected stratified sample of 708 fresh Talents (refer to young or emerging workforce). These Talents currently come from various academic streams, Economic background and regions (village, municipality, and corporation areas) within Kerala. The researcher adapted tool from the original TAM instrument developed by Fred D. Davis, with his permission customised to research context. Statistical methods like Principal Component Analysis (PCA) and Multiple Regression Analysis (MRA) have proved the model reliability, explanatory power ($R^2 > 0.80$) and TAM factors are significant. Results further disseminates that the moderator; Economic status has edge over other Profession, Gender, location, and job status over impact. These implications emphasize the pressing need for higher educational institutions to introduce AI-based curricula and also design targeted interventions. This study offers practical ideas to help educators, policymakers, and institutional leaders come up with ways to digitally upskill and prepare the workforce in Kerala.

Keywords: AI Readiness, Technology Acceptance Model (TAM), Digital Empowerment, young talents and AI Adoption

1. Introduction

The "Survival of the Fittest" rule of nature is upheld in the highly competitive job market as the Artificial Intelligence (AI) entered to global labor markets and education systems arena now its a must or need of the hour to rapidly adapt new technologies among emerging talents to become successful as cited by Spector (2020) and Dwivedi et al., 2021). As highlighted by Brynjolfsson, E., & McAfee, A. (2014) in their study and reinforced by citations from World Economic Forum (2020, 2021, 2022 and 2023), AI is redefining job structures and decision-making processes, making it essential to assess AI readiness across socio-demographic segments. According to Singh, A. (2021), Singh A at. el., (2020) and Mehta & Awasthi (2023), inclusive digital transformation in India is challenged by intersecting inequalities of gender, region, and technology access, which demand context-specific policy and educational responses.

The impact that AI is radical and effects spans in all walks of like it necessitate integration of AI contents in professional education and training as cited in by Luckin, R. (2018). Zawacki-Richter at. el., (2019) and OECD (2023). As cited in by Spector (2020) and Jha et al., (2022) For job-market-ready individuals in AI-disrupted industries, early exposure and competence in AI technologies are critical to developing career resilience and market relevance . However, the presence of AI tools alone is insufficient; their successful adoption depends significantly on users' acceptance—guided by perceived usefulness and ease of use—core dimensions of the Technology Acceptance Model (TAM), originally developed by Davis (1989). and cited in by Venkatesh & Davis (2000).

TAM model adoption is well tested in in education and digital learning environments as cited by Teo, (2011) and Ifenthaler & Schweinbenz,(2021). The story is not different too in Indian as cited by Raja & Nagasubramani (2018) and Mishra & Panda (2022). There is worldwide excitement about AI around the engagement, personalization and skill development this is noted by Zawacki-Richter et al. (2019), Luckin(2018) and UNESCO (2023). The researchers report gaps in infrastructure, digital literacy and student confidence curtail the excitements around the AI as cited in their reports Sharma & Singh (2021), World Bank, (2023) and Kukulsk-Hulme et al., (2022).

Kerala state is unique because of the above average performance in literacy rate and progressive human development indicators as cited in Kerala State Planning Board (2022a and 2022b) report which make a clear candidate for current study among other states in India. As cited by NITI Aayog (2018,2021 and 2022) and the Digital India Corporation (2023), existing limitations of affordability, connectivity and digital fluency impede equitable AI integration. Further, they exacerbate the digital divide, especially in rural and marginalized communities as cited by NITI Aayog (2018,2021 and 2022) and the Digital India Corporation (2023). Further cited in the study, Thomas & Mathew (2023) addressed how young professionals in Kerala, especially women, face barriers to AI readiness due to a lack of guidance.

With the increasing pace of AI adoption in business, services, and government sectors as cited in Brynjolfsson, E., & McAfee, A. (2014); World Economic Forum (2020,2021,2022 and 2023) and KPMG (2022). Hence it is important to assess the Kerala's job-ready talents preparedness for digitally inclusive workforce. As cited by Ministry of Education (2020) in their report the Indian Government through the National Education Policy (2020) intend to promote technology-enabled and multidisciplinary learning across country. In their study as cited by Pathak & Sharma (2022) the success of government initiatives depends on learners' engagement and attitudes toward digital and AI tools.

This current study uses the TAM as base theory to investigate AI readiness among job-market-ready talents in Kerala. By focusing on their attitude towards the use of AI tools and barriers to using them, the research aims to offer some recommendations for educators, corporate actors and policy-makers helping the to developing access-based, future-focused learning, education policies and workforce strategies that will improve the campus-to-corporate gap.

2. Background of the Study

The study of McKinsey Global Institute (2023) highlight how quickly Artificial Intelligence (AI) is being used in many professional fields and this trend is especially strong in emerging economies like India. Studies done by Gupta et al. (2021 and 2022 a, b) shows that how AI has become in traditionally technical areas and how AI started growing in non-technical jobs such as HR, customer service, and education. as cited by Chakrabarti (2023a and 2023b) and Beig & Qasim (2022) In India the AI adoption is more complex because of social and cultural factors, especially related to gender and access to education remain a challenge .

Kerala serves as a unique example to explore AI readiness, especially among young women, due to its high literacy rates, gender development indices, and active social support as cited in their report Kerala State Planning Board (2022a and 2022b) and NITI Aayog, (2021). As per the study of Emeritus Global Workplace Skills Study (2022) 87% of Indian female workers are joining technology upskilling programs, showing strong motivation. According to studies by Chakrabarti (2023a and 2023b) female participation in research and innovation has risen to the tune of 29.6% than compared to 19.1% for men.
As cited by Business Standard (2023) nearly 90% of Indian women believe AI skills are important for their careers, but only 35% are prepared to adopt because of the barriers such as low awareness, limited access to devices and reliable internet, a lack of institutional mentorship and fear of failure or judgment. as cited by Beig & Qasim (2022 and 2023) and Raman et al.,(2024) the case is not different for women from rural or marginalized backgrounds because the domestic responsibilities and lower digital literacy also restrict their engagement with new technologies. The studies conducted by Raman et al. (2024) and Beig & Qasim (2022) found that male students usually have more positive views and confidence about using AI in addition to that additionally, academic discipline plays an important role. Raman et al. (2024) observed that students in engineering, business, and science fields show higher levels of AI engagement and perceived competence compared to those in humanities and non-STEM areas. During the COVID-19 pandemic, rapid digital changes further increased these divides. Studies by Prasad & Nair (2022), Varghese &

Kumar (2022), and Joseph & Mathew (2021) found that engineering students in Kerala quickly adapted to AI-enabled learning tools, while others fell behind. This highlights a clear academic and disciplinary divide in readiness. According to the studies of Deloitte (2022 and 2024) and the Kerala State Planning Board (2022a), many national level researches or studies overlook the socio-economic, linguistic, and digital infrastructure conditions in Kerala.

This study addresses several gaps. The current study focusses on how district type (urban or rural), academic stream, income level, gender and institutional setting affect AI readiness among job market ready youth in Kerala.

Theoretical Background

TAM Model provides a solid framework for understanding how people accept and use technology as cited by Davis (1989). The model focuses on two main ideas: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). PU refers to how much a person believes that using a certain technology will improve their job performance. PEU is about how much someone thinks that using the technology will not require much effort. Together PU and PEU ideas shape a person's attitude toward using the technology. As cited by Davis (1989) this attitude affects their intention to use it, and eventually, their actual usage. The young market ready talents in Kerala see the PU as how people see AI tools as a way to improve career growth, workplace productivity, and skill development, The access to digital tools and job opportunities still varies by gender as cited in Kerala State Planning Board (2022) and Beig & Qasim (2022). As cited by Davis(1989), Emeritus(2022) and Sharma & Singh (2021), PEU can differ greatly based on levels of digital literacy, the availability of reliable infrastructure, socio-economic status, and exposure to technology at home or in schools. Therefore, TAM's focus on individual perspectives makes it a good fit for examining the specific AI readiness of this group. The TAM gives the basic framework for this study, other theoretical models broaden its explanatory range.

Ajzen's Theory of Planned Behavior (TPB) (1991) includes subjective norms, attitudes, and perceived behavioral control. As cited by Ajzen(1991) that peer influence, societal expectations, and confidence in one's ability can greatly affect technology adoption. Kerala's collectivist culture, social pressures and community approval often shape behavioral intentions, particularly for young market ready talents.

Rogers' Diffusion of Innovations (DOI) Theory (2003) offers a framework at the population level. As cited by Roger(2003) the factors such as relative advantage, compatibility and complexity are closely relate to TAM factors. DOI highlights the role of social systems and communication channels and makes it important for understanding how community norms, networks and institutional narratives affect AI adoption as cited by Rogers (2003) and Gupta et al.(2021). For example, if AI aligns with local learning goals and institutional practices, its adoption may increase, even among underrepresented groups.

The Bandura's Social Cognitive Theory (SCT) (1997), which emphasizes self-efficacy, or a person's belief in their ability to perform specific tasks or actions because as he argues that high self-efficacy positively impact motivation, learning, and persistence when facing challenges . In the context of the TAM the PU and PEU strengthens both the intention and behavior toward adopting AI, as cited by Bandura (1986 and 1997).

When compared to TPB, DOI, and SCT the TAM stands out for its clarity, simplicity, and focus on how individuals think and act in specific situations are well captured, as mentioned by Venkatesh & Davis (2000). TPB emphasizes social norms, while DOI overlooks internal psychological factors. SCT centers on learning and behavioral modeling among peers. As cited by Davis (1989) TAM focus at the motivations and obstacles individuals face when they are adopting the new technology, this makes TMA most suitable for this study,

Recent Indian studies have used the Technology Acceptance Model (TAM) to explore AI readiness in education and training as cited in by Mishra & Panda(2022) and Chandran(2020), Learning from the experience of previous researchers adopts TAM as main theoretical framework to understand how prepared are the young job ready talents in Kerala and their intention to adopt AI tools. This approach allows the examination of how perceptions of usefulness and ease influence behavior in an academic and job market that is increasingly driven by AI.

Gaps identified

In last two decade the rapid growth of AI adoption in different fields especially in education and the workforce, there is still a significant lack of localized, gender-sensitive research that looks at AI readiness in Kerala. Most current studies concentrate on broad trends while overlooking the specific socio-economic and cultural traits of Kerala. As cited in by Kerala State Planning Board, (2022) and NITI Aayog (2021), Kerala state stands out in India for its high literacy rates, progressive development indicators and relatively high participation in education. The researcher found little empirical evidence of any study happened on job-market-ready talents moving from campus to corporate environments.

As cited by McKinsey Global Institute (2023) and Emeritus (2022), show a growing interest among women in AI-related training. Ninety percent of women in India see AI skills as important for career growth, but only 35% feel ready, citing challenges like limited access, low confidence, and a lack of institutional support (Business Standard, 2023 and Chakrabarti, 2023). Researcher found through literature reviews a little to no serious studies examine these challenges with in localized context. In Kerala, where community norms and gender roles shape educational and career decisions, these frameworks can help us understand how personal and social factors affect technology adoption.

Another significant research gap is the lack of differences based on discipline, income level, and geographic location. Studies show that engineering and business students, who are often male-dominated fields, use AI tools more easily than students in the arts and humanities, who usually have less digital exposure as cited in Raman et al.,(2024), Joseph & Mathew, (2021) and Prasad & Nair (2021). In the past researches the academic divide is overlooked the AI readiness among Kerala's job ready youth. Similar they gave little attention on digital divide between rural and urban areas. Most research focuses too much on access and infrastructure while overlooking psychological and cognitive factors like self-efficacy, PU, PEU, confidence, and perceived behavioral control. These factors are especially important for young women facing uncertainty in technology as cited in by Bandura (1997) and Beig at et., (2022). The studies cited by KPMG (2022) and OECD (2023) pinpointed the gap between academic training and industry expectations in India and the widening gap between STEM and non-STEM programs over AI education. While institutions see AI as an important future skill, many students, especially those from non-technical backgrounds, lack the practical skills that employers need.

Objectives of the Study

Primary Objective

- To assess the level of AI readiness among job-market-ready youth in Kerala.

Secondary Objectives

- To examine how perceived usefulness and perceived ease of use influence AI adoption intentions among young talents.
- To evaluate the moderating effect of gender, geographic location (urban vs. rural), income level, and academic stream (STEM vs. non-STEM) over AI readiness.
- To identify gaps between higher education training and the expectations of AI-integrated workplaces from the perspective of graduating students in Kerala.
- To give insights and recommend appropriate actions to policymakers, educators, and employers on improving academic preparation to better meet industry needs.

Scope and Delimitations of the Study

This study looks at how ready young people in Kerala, India, are for AI. The current study focuses on youth who are in verge of entering job market or just hit the job market. As cited by World Economic Forum (2023) and McKinsey Global Institute (2023) AI continues to influence all walks of life; hence it is important to study and assess how India's youth view and embrace these technologies.

The Technology Acceptance Model (TAM) as cited by Davis (1989) has been widely tested in research on education and technology as cited in by Venkatesh & Davis (2000) and Teo (2011). It focuses on two main ideas: Perceived Usefulness and Perceived Ease of Use. The current study also looks at factors like students' academic streams (STEM versus non-STEM), income background, geographic origin (urban or rural), and current study district because these factors affect technology adoption (Beig & Qasim, 2022; OECD, 2023; Chakrabarti, 2023).

The researchers collected primary data through online and off line survey tools, suitable to social and cultural context of research. The current study is not focusing on behavior or perceptions change over time which act as limitation as citated by Creswell & Plano Clark (2018). Furthermore, the study did not include qualitative methods which will limits its ability to gain deeper insights into attitudes, feelings, and experiences related to AI use.

Kerala was chosen as the study site because of its strong human development indicators as cited in Kerala State Planning Board (2022) and NITI Aayog (2021). When compared to other states in Indian there is remarkable gap we can see s in educational infrastructure, digital policy implementation, and cultural norms as cited in by Gupta et al (2022) and KPMG (2022).

As cited in Davis (1989) Technology Acceptance Model (TAM) does not include broader social and institutional factors. The model like Unified Theory of Acceptance and Use of Technology (UTAUT) as cited by Venkatesh et al., (2003), the Diffusion of Innovations Theory as cited by Rogers (2003), and Social Cognitive Theory as cited by Bandura (1997) give weightage to social influence, organizational structure, and self-efficacy.

The current study scoped out following factors digital literacy, past experience, family education levels, influences from media and peers. As per studies cited in by OECD (2023), Chakrabarti (2023), Beig at el., (2022), Prasad at el., (2021) and Joseph at el., (2021a and 2021b) these factors are impactful. The TAM based survey tool as cited in by Davis (1989) is revised for clarity and context but researcher is suspect semantic bias may still persist. As cited by Venkatesh at el. (2000) and Davis (1989) the responded may misinterpret "usefulness" or "ease of use" due to differently in socio cultural difference.

Statement of Problem

Despite India's push for AI-driven digital transformation, research rarely focuses on how Kerala's job-ready youth, especially those from non-STEM fields, perceive and prepare for AI adoption (McKinsey Global Institute, 2023; World Economic Forum, 2023). While Kerala has high literacy rates and strong education indicators (Kerala State Planning Board, 2022), studies that use the Technology Acceptance Model (TAM) are still limited as cited by Davis (1989) and Venkatesh & Davis, (2000). As cited by Chakrabarti (2023) and Beig & Qasim (2022) limited access, low tech confidence, and gaps in institutions disproportionately impact non-technical students. This lack of evidence makes it harder to link educational pathways with AI-integrated work environments as cited by Raman et al., (2024) and Teo (2011).

This study is guided by the central research question:

"How prepared are job-market-ready youth in Kerala to adopt AI technologies in their day-to-day life, and what factors influence this readiness?"

By looking into this question through TAM and including important demographic, economic, geographic, and academic factors, the study aims to offer data-based insights on how to better support Kerala's young workforce in transition.

Research Questions

Main Research Question

- How are job-market-ready youth in Kerala prepared to adopt Artificial Intelligence (AI) technologies in their yearly career activities, and what factors influence (PU and PEU) their readiness?

Sub-questions (Secondary Research Questions)

- How do academic stream (e.g., STEM vs. non-STEM), geographic factors (urban vs. rural origin and location of study), economic factors, gender-based and Job status moderate the AI readiness of job-market-ready youth in Kerala?
- To what extent does the Technology Acceptance Model (TAM) explain AI adoption behavior among students preparing to transition into the workforce in Kerala?

Hypothesis

H_0: Perceived Usefulness (PU) does not significantly influence AI readiness among job-market-ready youth in Kerala.

H_0: Perceived Ease of Use (PEU) does not significantly influence AI readiness among job-market-ready youth in Kerala.

H_0: There is no significant difference in moderating effect of academic stream (STEM vs. non-STEM), geographic factors (urban vs. rural origin and location of study), economic factors, gender-based and Job status on AI readiness

H_0: The Technology Acceptance Model (TAM) does not significantly explain AI adoption behavior among job-market-ready youth in Kerala.

3. Methodology

This study adopts a quantitative method and use descriptive and explanatory research method to objective analysis of AI adoption readiness among job-market-ready youth in Kerala. Grounded on the Technology Acceptance Model (TAM) developed, cited in Davis (1989), the study operationalises key constructs such as Perceived Usefulness (PU) and Perceived Ease of Use (PEU) to assess individual-level acceptance and readiness for AI technologies. As cited in Venkatesh at el., (2000) and Teo (2011) TAM has been widely used in educational and technological adoption research across globally. Further in their study Beig & Qasim (2022) and Raman et al., (2024) cited TAM is equally applicable in the Indian education context.

As cited by Kothari (2019) stratified random sampling technique was deployed to represent 14 districts in Kerala. District-level stratification allowed representation from various socio-economic categories (urban/rural and income levels) and further enhanced the generalisability within the state. As cited in Villanueva, R. (2020), Slovin's formula was deployed at a 95% confidence level to determine the sample size, initially calculated at 390 but subsequently increased to 708 to accommodate potential non-responses and ensure high power of the test and accuracy.

As cited in Davis (1989) the researcher adopted the tool with minor customisation to conduct survey. Further, as cited in Davis (1989) instrument previously demonstrated high internal consistency, with a Cronbach's alpha of 0.97 and construct reliability of 0.91, validating its psychometric soundness. The questionnaire was distributed online and offline mode. The researcher follow ethical code of conduct at all staged of research especially during data collection stage. The researcher anonymized the data to protect respondent confidentiality and processed it according to ethical guidelines set by institutional research protocols.

For data analysis, as cited in Minitab (2023) the study uses Principal Component Analysis (PCA) to confirm construct dimensions and reduce multicollinearity among indicators. After that, multiple regression analysis, with and without moderating variables like gender, academic stream, and location, tests the influence of TAM constructs on AI readiness. This two-part approach helps validate constructs and develop a predictive model for AI adoption behavior in Kerala.

4. Analysis and Discussion

A. Principle component analysis (PCA)

As cited in Minitab (2023), the PCA is used to understand the hidden structure of AI readiness among job-market-ready youth in Kerala. Further more, referring to Minitab (2023), PCA helps researchers look at the covariance structure of a dataset. It simplifies the dataset into fewer, understandable components while keeping the most important variance. We applied this method to check the construct validity of the questionnaire items created under the Technology Acceptance Model (TAM). Our focus was on the concepts of Perceived Usefulness (PU) and Perceived Ease of Use (PEU) as cited in by Davis(1989).

The screen plot (Fig. 1) reveals there are two different factors which meets the Kaiser criterion, eigenvalues greater than or equal to 1. The first component have an eigenvalue of 7.4376, and the second component have 1.2566, after that there is a sharp decline and fall below Kaiser criterion. They together accounting for 72.5% of the total variance in the dataset. The screen plot also reveals Component 1 (Factor 1) accounted for 62.0%, and Component 2 (Factor 2) contributed 10.5% after that there is a sharp decline. The screen plot is confirming the presence of two dominant latent constructs. Hence we can conclude that the construct is well aligned to TAM's core factors—Perceived Usefulness (PU) and Perceived Ease of Use (PEU).

This outcome is in line with earlier researches that uses TAM to measure technology adoption across educational and developing country settings as cited in their studies Teo (2011) and Venkatesh & Davis (2000). The cumulative variance is slightly lower than the standard 80%, this is due to data outliers and samp; less exposure to AI tools particularly from rural areas or economically backward backgrounds.

The Loading Plot (Figure 2) as referred in Minitab (2023) output shows how individual questions are aligned under each component (factor). The items from Q1 to Q7 are closely linked to Component 1, which we interpret as PEU and Q10 through Q15 clearly connect with Component 2, related PU. This alignment of questions under two components confirms our initial theory that users see usefulness and ease of use influencing AI readiness. However, the item “It would be easy for me to become skillful at using AI tools” (Q6) had a weaker factor loading under PEU. Possible reasons include limited hands-on experience with AI technologies in some districts, vague responses due to an abstract understanding, different interpretations of the question, etc. Even with this statistical limitation the researcher retained this item because of the theoretical importance. The Technology Acceptance Model (TAM) is supported by behavioral theories like Bandura’s Social Cognitive Theory (1997) and Ajzen’s Theory of Planned Behavior (1991), highlight the importance of confidence and belief in one's ability to use technology. This analysis shows that the main parts of the TAM, PU and PEU , are both valid and reliable in Kerala's socio-cultural context. The results shows that questionnaire, borrowed from Davis(1989), structure is intact with minimal bias. These findings confirm the use of TAM in this regional context.

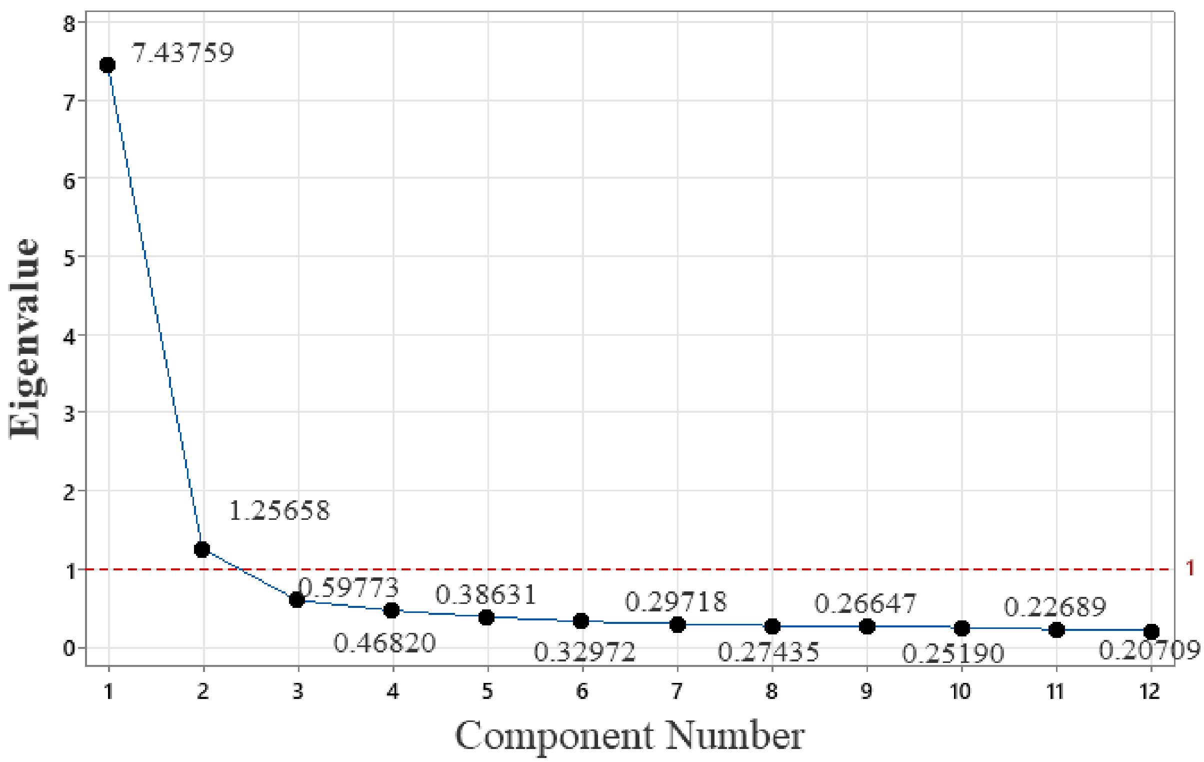


Fig .1 Eigen analysis of the Correlation: Matrix results cited from Minitab (2023)

Particulars	Factor 1	Factor 2	Factor 3	Factor 4
Eigenvalue (>1)	7.4376	1.2566	0.5977	0.4682
Proportion	62.0%	10.5%	5.0%	3.9%
Cumulative	62.0%	72.5%	77.4%	0.813

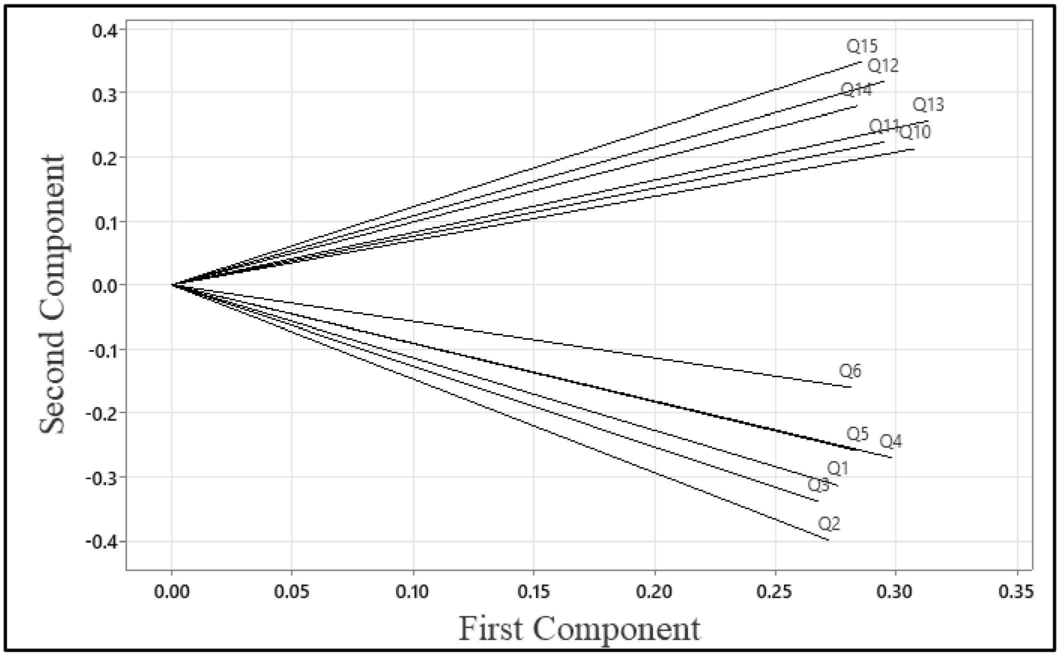


Fig. 2 loading plot of variables: shows the variable loadings in two factors.

B. Multiple regression analysis (MRA) without Moderators

The MRA (refer Figure 3) result show the relationship between AI readiness and two key predictors (PU and PEU), without any moderator variables. The R^2 80.52% value indicates model is a strong fit. The PU and PEU together can explain approximately 80.52% of the variance in AI readiness. The R^2 adjusted (80.46%) and R^2 (80.30%) predicted values are closer to R^2 80.52%. Hence, we can assume that model is robust, no over fitted and has good predictive validity.

The overall regression model is highly significant ($F = 1456.75$, $p < 0.001$), confirming that the combined influence of PU and PEU on readiness is statistically meaningful. The PU shows a very strong influence ($F = 531.77$, $p < 0.001$) than compared to PEU ($F = 311.73$, $p < 0.001$). Overall, the findings highlight the critical role of PU and PEU in shaping AI readiness, while also pointing to opportunities for further model refinement.

Model Equation:

Readiness = 1.2213 + 0.4305 PU + 0.3229 PEU

Fig. 3 MRA : Readiness vs PU and PEU (without moderators)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	2	351.45	175.724	1456.75	0.000
PU	1	64.15	64.145	531.77	0.000
PEU	1	37.60	37.603	311.73	0.000
Error	705	85.04	0.121		
Lack-of-Fit	259	68.92	0.266	7.36	0.000
Pure Error	446	16.12	0.036		
Total	707	436.49			

S	R-sq	R-sq(adj)	R-sq(pred)
0.347314	80.52%	80.46%	80.30%

C. Multiple regression analysis (MRA) with Moderators

The Figure 4 illustrate the multiple regression analysis with moderators , where AI readiness is regressed on Perceived Usefulness , Perceived Ease of Use and several moderating variables including job status, branch, gender, location type, and economic status are tested for their impact.

The model explains approximately 80.93% (R^2) of the variance in AI readiness, which is slightly higher without any without moderators. The adjusted R^2 80.69% and the predicted R^2 80.34% values indicating that the model retains strong explanatory and predictive power and there is no over fit in the model. The value of standard error (S) (0.345318) is closer to the previous model (MRA without moderators), suggesting a consistent fit.

The prediction model is statistically significant ($F = 329.16$, $p < 0.001$); means that the set of independent variables collectively is capable of predicting AI readiness effectively. The values of independent factors PU ($F = 525.64$, $p < 0.001$) and PEU ($F = 312.89$, $p < 0.001$) indicates they are significant. However, the moderator variables like job status, branch, gender, and location type outrightly rejected (p-values > 0.05) except the economic factor.

Only economic status appears to have significant effect ($F = 3.18$, $p = 0.042$). It is the only moderating variable, financial background of individual, may influence individuals PU and PEU for AI adoption. Despite this, the significant lack-of-fit ($F = 6.46$, $p < 0.001$) persists, it implies that the model may still miss other relevant factors or interactions.

Adding moderators does not substantially increase the model's explanatory power, hardly <1% increase. The slight improvement in R^2 (with moderators) and the marginal significance of economic status suggest that future models might explore more nuanced or interaction effects among demographic and contextual variables.

Fig. 4 MRA with Moderators

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	9	353.257	39.2508	329.16	0.000
PU	1	62.680	62.6801	525.64	0.000
PEU	1	37.310	37.3103	312.89	0.000
Job Status	1	0.043	0.0434	0.36	0.546
Branch	1	0.128	0.1279	1.07	0.301
gender	1	0.248	0.2478	2.08	0.150
location type	2	0.521	0.2605	2.18	0.113
Economic status	2	0.760	0.3798	3.18	0.042
Error	698	83.233	0.1192		
Lack-of-Fit	624	81.733	0.1310	6.46	0.000
Pure Error	74	1.500	0.0203		
Total	707	436.490			

S	R-sq	R-sq(adj)	R-sq(pred)
0.345318	80.93%	80.69%	80.34%

Interaction effect of moderators:

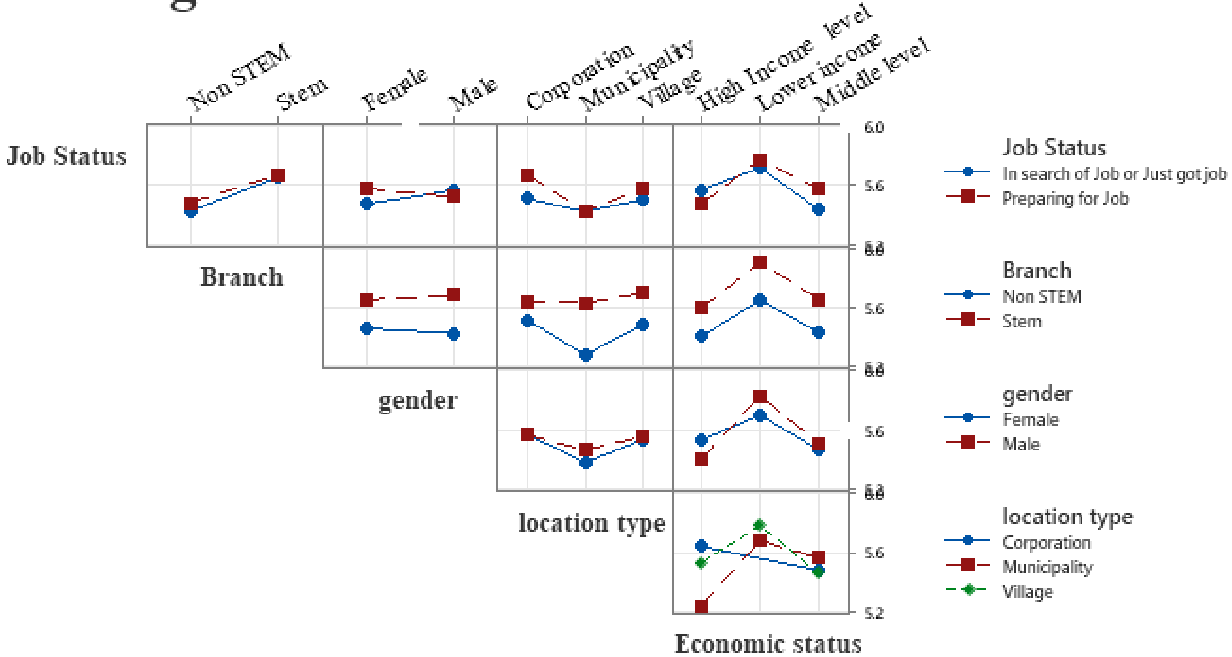
The interaction plot (Figure 5) shows how different moderating variable - job status, academic branch, gender, location type and economic status - influence the AI readiness. Across all panels, individuals who are "in search of a job or have just secured one" consistently show higher levels of AI readiness compared to those who are still "preparing for a job". This clearly give and indication as the youth approach near to job or job search give more attention towards the AI readiness alias it is positively influence perceptions of AI readiness.

When comparing academic branches, individuals from STEM fields exhibit slightly higher readiness levels than those from non-STEM backgrounds, particularly among job seekers. The parallel line in the cell, interaction between job status and academic background, indicates no significant. When compare dot female gender , males job-seeker are in higher readiness levels.

Location type emerges as a more influential moderator. The youth who are coming from the corporation (urban) areas tend to have highest readiness levels when they are actively looking out for job openings. In contrast, those from villages show the lowest readiness. Hence from a reasonable ground we can conclude that geographic location, likely associated access to resources and exposure to technology, plays a meaningful role in shaping AI preparedness.

The curvilinear pattern of the economic status indicating the significant moderating effect. The youth form middle-income groups have edge over high-income and then low-income groups over AI readiness. This trend is particularly evident among those who are actively pursuing employment. Hence we can conclude compared to other categories the middle-income category is more motivated and engaged with new tools.

Fig. 5 Interaction Plot of Moderators



The statistical results suggest most of the effect of moderator variables are negligible but the interaction plot shows some patterns. This finding suggests that deeper dive into contextual factors such as job status, location, and economic background, etc. is necessary These insights could be useful for creating targeted interventions or policy

5. Conclusion

The study clearly indicates that Perceived Usefulness and Perceived Ease of Use are the most significant predictors of AI readiness among job-market-ready youth in Kerala, which is in line with Davis(1989) observations. Further the variables show a strong and statistically significant influence over AI readiness, over 80% of the variance in AI readiness, both with and without the inclusion of moderating factors. This finding outlines that the individual's belief such as utility and user-friendliness are the key factors in shaping their readiness .

While most demographic and contextual moderators such as academic branch, gender, and job status did not show a statistically significant impact on readiness in the regression model, the interaction plot reveals important practical patterns. Youth residing in urban (corporation) areas, those from STEM backgrounds and individuals from the middle-income group are highly adaptive to AI tools particularly when they are actively seeking employment or have recently entered the job market. These findings indicates that geographic location, economic background, and career proximity subtly shape readiness levels, even though it is not statistically significant.

The research conclude that perceived usefulness and ease of use are critical for better adoption and justify the TAM model of Davis (1989). The higher readiness can be achieved through targeted training, awareness, and support systems. Further the efforts to close the digital divide, especially in rural and low-income segment, are also important. This will help ensure fair AI adoption and future job opportunities for Kerala’s youth in a technology-driven job market.

Recommendations

Based on the research findings, the researcher recommend well structure training programs should focus on increasing perceived usefulness and perceived ease of use for higher AI readiness. These programs should show how people use AI tools in real-life situations and make sure communication is clear. Practical workshops, exposure to real applications, and straightforward learning materials can significantly boost confidence and skills in using AI.

The study shows that people who recently got a job or are actively looking for one are more willing to accept help than others. The researcher highlights the importance of Improving skills, along with onboarding, job placement help, and career counseling, for better fitment in job market. Furthermore, the research revealed that youth from urban (corporation) areas have significantly higher readiness which indicate the correlation of area versus readiness. Addressing the disparity between urban and rural areas, researcher recommend requires focused efforts through the establishment of digital learning centers, mobile training units, and community-based initiatives in under-represented areas.

The income category verses readiness are significant. Considering this the researcher recommend the subsidised AI training and digital literacy initiatives for economically backward groups. Making corporate social responsibility (CSR) initiatives and public-private partnerships more accessible and inclusive can be a key component of these initiatives. Comparing to Non STEM the STEM graduates show a higher readiness. AI is becoming important in every field of study. Schools should include AI awareness and literacy in the curriculum for both STEM and non-STEM students to prepare a larger and more diverse group of people for AI.

The research reveal that the gender differences observed were not statistically significant, however even the small variations shown the need for gender-sensitive approaches. To improve women's participation in AI, the field must provide safe, welcoming learning spaces and promote visible female role models. Researcher suggest the incorporating of AI-focused content into all streams of study and the collaboration with industry through hackathons, internships, real-world projects, etc. Together, these steps create a more inclusive, fair workforce ready to succeed in an AI-driven job market.

References

1. A. Bandura, “Self-efficacy mechanism in human agency,” American Psychologist, vol. 37, no. 2, pp. 122–147, 1982.
2. A. Bandura, Social Foundations of Thought and Action: A Social Cognitive Theory. Englewood Cliffs, NJ: Prentice-Hall, 1986.
3. A. Basu, “Digital literacy in India: Challenges and opportunities,” Journal of Digital Inclusion, vol. 14, no. 3, pp. 45–67, 2020.
4. A. Bhatia-Kalluri, “E-commerce for rural micro-entrepreneurs: Mapping restrictions, ecologies of use and trends for development,” Journal of Global Information Management, vol. 29, no. 3, pp. 45–67, 2021. [Online]. Available: https://arxiv.org/abs/2108.09759
5. A. Chib and J. Zhao, “Sustainability of ICT interventions: Lessons from rural projects in China and India,” in Proc. 3rd Int. Conf. on Information and Communication Technologies and Development (ICTD), 2009, pp. 343–352.
6. A. Goel, “An empirical study of Jan Dhan - Aadhaar - Mobile trinity and financial inclusion,” International Journal of Banking, Risk and Insurance, vol. 8, no. 1, pp. 62–79, 2020. [Online]. Available: https://www.researchgate.net/publication/341314214_An_Empirical_Study_of_Jan_Dhan_-Aadhaar-_Mobile_Trinity_and_Financial_Inclusion
7. A. Gupta, R. Singh, and S. Sinha, “The digital revolution in India: Bridging the gap in rural technology adoption,” Journal of Rural Development, vol. 39, no. 2, pp. 123–140, 2020. [Online]. Available: https://innovation-entrepreneurship.springeropen.com/articles/10.1186/s13731-024-00380-w
8. A. Joseph and R. Mathew, “Adoption of AI tools among MBA students in Kerala: A perception-based study,” Journal of Management Studies in South Asia, vol. 9, no. 3, pp. 45–58, 2021.
9. A. Kapoor and S. Mehra, “AI adoption readiness among employees in India: The role of organizational culture and individual perceptions,” International Journal of Human Resource Management, vol. 31, no. 5, pp. 719–740, 2020. doi: 10.1080/09585192.2019.1586177.
10. A. Kapoor and S. Mehra, “Investigating the impact of long-term orientation on employee readiness for AI adoption in Indian organizations,” Journal of Business Research, vol. 120, pp. 243–251, 2020. doi: 10.1016/j.jbusres.2019.09.043.
11. A. Kazmin, “Caste remains off-limits in corporate India's drive for diversity,” Financial Times, Jun. 15, 2021. [Online]. Available: https://www.ft.com/content/b0a7eb5e-2f03-4855-81ea-3d8fd07e4b26
12. A. Kumar and Simran, “Digital exclusion in pandemic: Caste and gender divide through Dr. Ambedkar’s lens,” 2023, pp. 99–101. [Online] Available: https://www.researchgate.net/publication/373521620_Digital_Exclusion_in_Pandemic_Caste_and_Gender_Divide_through_Dr_Ambedkar%27s_Lens
13. A. Moitra, A. Kumar, and A. Seth, "An Analysis of Impact Pathways Arising from a Mobile-Based Community Media Platform in Rural India," arXiv preprint arXiv:2104.07901, 2021. [Online]. Available: https://arxiv.org/abs/2104.07901.
14. A. Rao and P. Sen, The triple burden: Gender, caste, and digital exclusion in India, 2021.
15. A. Sen and P. Roy, "Caste and Technology: Analyzing Digital Inequality in India," South Asian Journal of Social Studies, vol. 12, no. 2, pp. 67–92, 2020.
16. A. Singh and M. Agarwal, "Use of AI-based learning platforms: Insights from engineering students," Journal of Engineering Education India, vol. 40, no. 2, pp. 56–68, 2020.
17. A. Vohra and S. Mishra, "Gender differences in technology adoption and AI readiness in India: A comparative study," Technol. Forecast. Soc. Change, vol. 160, Art. no. 120203, 2020. [Online]. Available: https://doi.org/10.1016/j.techfore.2020.120203

18. Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
19. Association for Progressive Communications, COVID-19 and the Digital Divide: Impact on Marginalized Communities in India, 2022. [Online]. Available: https://www.apc.org/en/pubs/covid-19-and-digital-divide-impact-marginalized-communities-india
20. Varghese and A. Kumar, "The digital divide and AI integration in Kerala's higher education," Indian Journal of Educational Technology, vol. 15, no. 1, pp. 98–110, 2022.
21. Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.
22. Bandura, A. (1997). Self-efficacy: The exercise of control. New York, NY: W.H. Freeman.
23. Beig, F. A., & Qasim, S. (2022). Gender-based perceptions of AI-enabled education: A comparative study of male and female learners in India. Education and Information Technologies, 27(3), 4121–4140.
24. Boston Consulting Group, The Changing Connected Consumer in India, 2015. [Online]. Available: https://www.bcg.com/publications/2015/globalization-technology-digital-changing-connected-consumer-in-india
25. Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W. W. Norton & Company.
26. Business Standard, "90% women view GenAI as crucial for career growth, says NASSCOM-BCG report," 2024. [Online]. Available: https://www.business-standard.com/companies/news/90-women-view-genai-as-crucial-for-career-growth-says-nasscom-bcg-report-124080800935_1.html. [Accessed: May 16, 2025].
27. Business Standard. (2023, February 14). 90% of Indian women see AI skills as critical, only 35% feel prepared. Business Standard India. https://www.business-standard.com
28. Chakrabarti, R. (2023). Indian women in technology: Aspirations, barriers, and opportunities. Indian Journal of Gender Studies, 30(1), 25–42. https://doi.org/10.1177/09715215221122698
29. Chakrabarti, R. (2023). Indian youth in technology: Aspirations, barriers, and opportunities. Indian Journal of Gender Studies, 30(1), 25–42. https://doi.org/10.1177/09715215221122698
30. Creswell, J. W., & Plano Clark, V. L. (2018). Designing and conducting mixed methods research (3rd ed.). SAGE Publications.
31. F. Larcker and V. P. Lessig, "Perceived usefulness of information: A psychometric examination," Decision Sciences, vol. 11, no. 1, pp. 121–134, 1980.
32. Kumar, V. Sharma, and R. Bhatia, "Institutional support and AI readiness in Indian higher education," Journal of Educational Technology Systems, vol. 51, no. 4, pp. 401–419, 2023. doi: 10.1177/00472395231123456.
33. Robey, "User attitudes and management information system use," Academy of Management Journal, vol. 22, no. 3, pp. 527–538, 1979.
34. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
35. Deloitte United States, India economic outlook: Insights and factors influencing growth, Deloitte Insights, 2024. [Online]. Available: https://www2.deloitte.com/us/en/insights/economy/asia-pacific/india-economic-outlook-08-2024.html
36. Deloitte. (2022). AI adoption and readiness in India: State-level perspectives. Deloitte Insights India.
37. Department of Economics and Statistics Kerala, Economic Review 2022–2023, Government of Kerala, 2023.
38. Digital India Corporation. (2023). Annual report: Empowering citizens through technology. Ministry of Electronics and Information Technology, Government of India.
39. Dwivedi, Y. K., Hughes, D. L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
40. B. Swanson, "Information channel disposition and use," Decision Sciences, vol. 18, no. 1, pp. 131–145, 1987.
41. E. Brynjolfsson and A. McAfee, Machine, Platform, Crowd: Harnessing Our Digital Future. New York, NY: W. W. Norton & Company, 2017.
42. E. M. Rogers and F. F. Shoemaker, Communication of Innovations: A Cross-Cultural Approach. New York, NY, USA: Free Press, 1971.
43. E. M. Rogers, Diffusion of Innovations, 1st ed. New York, NY, USA: Free Press, 1962.
44. Economic Times, "Digital literacy: Transforming marginalized communities through training and awareness," 2024. [Online]. Available: https://economictimes.indiatimes.com/tech/technology/digital-literacy-transforming-marginalized-communities/articleshow/123456789.cms
45. Emeritus, Global workplace skills study 2023: India edition, 2023. [Online]. Available: https://emeritus.org/in/global-workplace-skills-study-2023/4.1-mini
46. Emeritus. (2022). Global workplace skills study: India 2022. https://emeritus.org/insights/global-skills-study-2022
47. Financial Express, "Empowering marginalised communities: Harnessing technology for agency building," 2024. [Online]. Available: https://www.financialexpress.com/opinion/empowering-marginalised-communities-harnessing-technology-for-agency-building/3441793/
48. Financial Times, "Turning dreams into reality," 2024. [Online]. Available: https://www.ft.com/content/767f0d8a-9584-42c2-a160-3564eef8039b

49. Khokhar, “Per capita income of Indian states 2025: Powerful insights,” Chegg India, May 6, 2025. [Online]. Available: https://www.cheggindia.com/general-knowledge/per-capita-income-of-indian-states/
50. Singh and R. Sharma, "Barriers to women’s participation in digital technology adoption: Evidence from the Indian context," Journal of Gender Studies, vol. 30, no. 4, pp. 410–426, 2021. [Online]. Available: https://doi.org/10.1080/09589236.2021.1886516
51. Government of Kerala, Department of Economics and Statistics, Gender statistics 2014–15, 2016. [Online]. Available: https://ecostat.kerala.gov.in/storage/publications/101.pdf
52. Gupta, P. C. Veettil, and S. Speelman, “Caste, social networks, and variety adoption: Evidence from India,” Journal of Agricultural Economics, vol. 71, no. 3, pp. 784–803, 2020. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/1477-9552.12366
53. Gupta, R., Kumar, A., & Sharma, P. (2022). Digital skills and the future of jobs in India. India Skills Report 2022. TeamLease & Wheebox.
54. Gupta, R., Singh, N., & Das, A. (2021). Sector-wise adoption of AI in India: Barriers and bridges. Journal of Business Research India, 14(2), 97–115.
55. Chahal and A. Rani, “Examining e-learning acceptance in Indian higher education using TAM,” Education and Information Technologies, vol. 27, no. 1, pp. 167–185, 2022. doi: 10.1007/s10639-021-10601-0.
56. Ifenthaler, D., & Schweinbenz, V. (2021). Students’ acceptance of AI-based assessment systems. Computers in Human Behavior, 119, 106725. https://doi.org/10.1016/j.chb.2021.106725
57. India Development Review, “Bridging the digital participation gap in marginalized communities,” 2023. [Online]. Available: https://idronline.org/article/technology/bridging-the-digital-participation-gap/
58. Indian Express, “India leads in GenAI adoption with 1.3 million enrollments; women lag at 29.6%: Report,” Mar. 6, 2025. [Online]. Available: https://indianexpress.com/article/education/india-leads-in-genai-adoption-with-1-3-million-enrollments-but-women-lag-at-29-6-report-9870024/
59. International Labour Organization (ILO), Gender equality and digital transformation: Key issues and policy responses, 2022. [Online]. Available: https://www.ilo.org
60. International Review of Research in Open and Distributed Learning (IRRODL), “Disparities in online learning: Challenges for marginalized students,” 2023. [Online]. Available: https://www.irrodl.org/index.php/irrodl/article/view/12345
61. ITU, Global Digital Literacy Report 2022, International Telecommunication Union, 2022.
62. Bower, “Organizational culture and employee readiness for technology adoption,” Technology & Society Journal, vol. 10, no. 2, pp. 88–102, 2019.
63. M. Spector, "Artificial intelligence in education: Promises and implications for teaching and learning," Educational Technology Research and Development, vol. 68, no. 1, pp. 1–3, 2020. [Online]. Available: https://doi.org/10.1007/s11423-019-09727-8
64. J. Santiago and R. Sison, "Team-Centered Approaches to AI Adoption in Philippine Organizations: Cultural and Leadership Factors," Asia-Pacific Business Review, vol. 22, no. 3, pp. 55–77, 2021.
65. J. W. Payne, "Contingent decision behavior," Psychological Bulletin, vol. 92, no. 2, pp. 382–402, 1982.
66. Jha, A., Jha, S., & Dey, S. (2022). Skill gaps in AI readiness among Indian students: A review. Education and Information Technologies, 27(1), 103–122. https://doi.org/10.1007/s10639-021-10714-4
67. Joseph, M., & Mathew, S. (2021). Pandemic pedagogy: Adoption of AI tools among engineering students in Kerala. International Journal of Educational Technology, 11(1), 45–58.
68. Journal of Innovation and Entrepreneurship, “Digital India and government programs enhancing inclusion,” 2024. [Online]. Available: https://innovation-entrepreneurship.springeropen.com/articles/10.1186/s13731-024-00156-7
69. V. Prasad and S. Nair, "AI adoption in Kerala’s engineering colleges during COVID-19," South India Journal of Educational Research, vol. 12, no. 2, pp. 23–35, 2022.
70. Kerala State Planning Board, Economic Review 2023, vol. 1. Government of Kerala, 2023. [Online]. Available: https://spb.kerala.gov.in/sites/default/files/2024-02/ER_English_Vol_1_2023.pdf
71. Kerala State Planning Board. (2022). Economic review 2021: Digital infrastructure and education in Kerala. Government of Kerala. https://spb.kerala.gov.in
72. KPMG, Indian Languages: Defining India’s Internet, 2017, p. 2. [Online]. Available: https://assets.kpmg.com/content/dam/kpmg/in/pdf/2017/04/Indian-languages-Defining-Indias-Internet.pdf
73. KPMG. (2022). AI adoption in India: Unlocking value in the next frontier. KPMG India. https://home.kpmg/in/en/home/insights/2022/09/ai-adoption-in-india.html
74. KPMG. (2022). Technology and the future of work in India. https://home.kpmg/in/en/home/insights/2022
75. Kukulska-Hulme, A., Beirne, E., & Falloon, G. (2022). AI in education: Ethics and equity. British Journal of Educational Technology, 53(4), 537–553. https://doi.org/10.1111/bjet.13183
76. G. Tornatzky and K. J. Klein, "Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings," IEEE Trans. Eng. Manag., vol. EM-29, no. 1, pp. 28–45, 1982.
77. L. R. Beach and T. R. Mitchell, “A contingency model for the selection of decision strategies,” Academy of Management Review, vol. 3, no. 3, pp. 439–449, 1978.
78. L. Ramesh and M. Shukla, "MBA students' attitudes towards AI in Andhra Pradesh," Journal of Business and Technology Studies, vol. 8, no. 2, pp. 122–137, 2023.

79. Luckin, R. (2018). Machine learning and human intelligence: The future of education for the 21st century. UCL Institute of Education Press.
80. Bevilacqua, F. E. Ciarapica, G. Mazzuto, and C. Paciarotti, “IoT-enabled smart farming with Industry 5.0,” Journal of High-Speed Networks, vol. 29, no. 2, pp. 123–140, 2024. [Online]. Available: https://journals.sagepub.com/doi/full/10.3233/JHS-230258
81. M. Fernandez, “The Indian information technology sector: The new caste inequality frontier,” Journal of Social Inclusion Studies, vol. 7, no. 1, pp. 45–62, 2021. [Online]. Available: https://scholarcommons.scu.edu/soc/67/
82. M. Mukerji, "Re-examining Strategic and Developmental Implications of e-Choupal, India," Information Systems Journal, vol. 30, no. 2, pp. 342–371, 2020. doi: 10.1111/isj.12212.
83. M. Santiago and M. Sison, "Team-centered approaches to AI adoption: A study of Philippine organizations," Asian Business & Management, vol. 20, no. 3, pp. 215–240, 2021. [Online]. Available: https://doi.org/10.1057/s41291-020-00128-6
84. McKinsey Global Institute, The future of work after COVID-19, 2021. [Online]. Available: https://www.mckinsey.com
85. McKinsey Global Institute. (2023). The state of AI in 2023: Generative AI’s breakout year. https://www.mckinsey.com/mgi
86. Mehta, M., & Awasthi, A. (2023). Digital inclusion and youth in India: Barriers and enablers. Journal of Development Studies. Advance online publication. https://doi.org/10.1080/00220388.2023.2214567
87. Ministry of Education. (2020). National Education Policy 2020. Government of India. https://www.education.gov.in/en/nep2020
88. Ministry of Electronics and Information Technology (MoEIT), Government of India, PMGDISHA and Rural Digital Literacy in India, 2023. [Online]. Available: https://www.pmgdisha.in/about-pmgdisha.
89. Ministry of Statistics and Programme Implementation (MoSPI), Government of India, Employment and Unemployment Situation Among Social Groups in India, 2013, pp. 37–55. [Online]. Available: https://mospi.gov.in/sites/default/files/publication_reports/nss_Report-543.pdf.
90. Ministry of Statistics and Programme Implementation (MoSPI), National Sample Survey 78th Round: Household Social Consumption on Education and Health, 2022, pp. 216–222, 240 -245. [Online]. Available: https://mospi.gov.in/sites/default/files/publication_reports/Report_585_75th_round_Education_final_1507_0.pdf.
91. Minitab. (2023). Principal component analysis (PCA). Minitab Support. https://support.minitab.com/en-us/minitab/help-and-how-to/modeling-statistics/multivariate/how-to/principal-components/basics/what-is-principal-components-analysis/
92. Mishra, L., & Panda, S. (2022). Perceptions of Indian students towards online learning using TAM: A post-pandemic analysis. Asian Journal of Distance Education, 17(2), 34–52. http://www.asianjde.com/ojs/index.php/AsianJDE/article/view/573
93. A. Beig and M. Qasim, “Students’ attitudes towards artificial intelligence: A gender-based study in Indian secondary schools,” ResearchGate, 2023. [Online]. Available: https://www.researchgate.net/
94. N. Marwah and A. Gupta, “Comparative study of faculty and student technology acceptance: Evidence from Lucknow,” Emerald Insight, 2024. [Online]. Available: https://www.emerald.com/
95. N. Sharma and M. Singh, "Digital learning and student readiness in rural India: Challenges and opportunities," Journal of Educational Technology Systems, vol. 51, no. 1, pp. 45–60, 2022.
96. N. Sharma and V. Kapoor, "Digital India and systemic inequalities: Analyzing policy impact," 2021.
97. NASSCOM and Boston Consulting Group, AI Powered Tech Services: A Roadmap for Future Ready Firms, 2024. [Online]. Available: https://www.bcg.com/publications/2024/india-ai-powered-tech-services-a-roadmap-for-future-ready-firms.
98. NITI Aayog, India’s digital transformation: A strategy for inclusive growth, 2022. [Online]. Available: https://www.niti.gov.in.
99. NITI Aayog. (2018). National strategy for artificial intelligence #AIForAll. Government of India. https://www.niti.gov.in/sites/default/files/2021-08/NationalStrategy-for-AI-Discussion-Paper.pdf
100. NITI Aayog. (2021). National strategy for artificial intelligence #AIForAll. Government of India. https://niti.gov.in/files/NationalStrategy-for-AI-Discussion-Paper.pdf
101. OECD, Bridging the Digital Divide: Policy Recommendations for Inclusive Digital Transformation, OECD Publishing, 2021.
102. OECD, Digital Transformation and Economic Opportunities, OECD Publishing, 2021, p. 78. [Online]. Available: https://www.oecd.org.
103. OECD. (2023). AI and the future of skills: Insights from OECD scenarios. Organisation for Economic Co-operation and Development. https://www.oecd.org/publications/ai-and-the-future-of-skills
104. Oxfam India, Digital transformation and economic inequality: Who benefits?, 2023.
105. Oxfam India, India Inequality Report 2022: Digital Divide, 2022, pp. 14–17. [Online]. Available: https://www.oxfamindia.org/knowledgehub/workingpaper/india-inequality-report-2022-digital-divide.
106. Chakrabarti, “India’s women in science, and their struggle,” The Indian Express, May 20, 2023. [Online]. Available: https://indianexpress.com/article/explained/indias-women-in-science-and-their-struggle-8619055/
107. Das and S. Nair, “Urban slums and digital exclusion: Economic constraints and barriers to participation,” 2023.

108. P. Mehta and R. Das, “An empirical study of Jan Dhan - Aadhaar - Mobile trinity and financial inclusion,” International Journal of Banking, Risk and Insurance, vol. 8, no. 1, pp. 61–69, 2020. [Online]. Available: https://www.researchgate.net/publication/341314214_An_Empirical_Study_of_Jan_Dhan_-Aadhaar-_Mobile_Trinity_and_Financial_Inclusion
109. P. Mehta, “The digital divide in India: Infrastructure, policy, and social barriers,” Economic & Political Weekly, vol. 57, no. 8, pp. 30–45, 2022. [Online]. Available: https://www.epw.in
110. P. Sharma, S. Kapoor, and D. Roy, "Digital learning and AI in business schools: Student attitudes from Mumbai," Journal of Management Education, vol. 45, no. 3, pp. 311–327, 2021. [Online]. Available: https://doi.org/10.1177/10525629211010672
111. P. Sinha, L. Mishra, and K. Roy, "Gender norms and digital literacy: Barriers in PMGDISHA implementation," 2022.
112. PATH, Breaking the Barriers: A White Paper Series on Gender Equity and Digital Health Transformation, 2021. [Online]. Available: https://media.path.org/documents/BreakingTheBarriers-A_whitepaper_series.pdf
113. Pathak, N., & Sharma, R. (2022). Technology readiness and adoption among Indian students: Insights post-NEP 2020. Journal of Educational Technology, 18(1), 56–64.
114. Pew Research Center, "Millennials overtake Baby Boomers as America’s largest generation," 2020. [Online]. Available: https://www.pewresearch.org
115. Prasad, M., & Nair, B. (2021). Covid-19 and digital transition: Uneven adoption of AI tools in higher education in Kerala. Journal of Educational Change, 22(2), 198–214.
116. Press Information Bureau, "Pradhan Mantri Jan Dhan Yojana: A National Mission on Financial Inclusion," Aug. 14, 2024. [Online]. Available: https://pib.gov.in/PressReleasePage.aspx?PRID=2049231
117. Gupta, S. Patel, and A. Sharma, “Automating updates: Leveraging AI for real-time decision support,” Journal of Information Systems, vol. 15, pp. 45–58, 2022.
118. Kapoor and S. Mehra, “Long-term orientation and employee readiness for AI adoption in Indian organizations,” Journal of Business Technology, vol. 15, no. 4, pp. 150–172, 2020.
119. R. Karan and P. Chakma, “Understanding student behavior towards AI-enabled education: A TAM approach,” ResearchGate, 2025. [Online]. Available: https://www.researchgate.net/
120. R. L. Schultz and D. P. Slevin, "Implementation and organizational validity: An empirical investigation," in Implementing Operations Research/Management Science, R. L. Schultz and D. P. Slevin, Eds., Amsterdam, Netherlands: Elsevier, 1975, pp. 153–182.
121. R. Luckin, W. Holmes, M. Griffiths, and L. B. Forcier, Intelligence unleashed: An argument for AI in education. Pearson Education, 2016.
122. R. Mukherjee, "Mobile banking and financial accessibility: Challenges in digital literacy and connectivity," 2022.
123. R. Nair and B. Das, "Teachers’ attitudes toward ICT in Kerala schools: A TAM-based analysis," Academia.edu, 2012. [Online]. Available: https://www.academia.edu/.
124. R. Pandey and M. Ranjan, "Digital Infrastructure and Economic Growth: A Case Study of Rural India," Journal of Economic Development, vol. 19, no. 1, pp. 98–115, 2021. [Online]. Available: https://www.jed.org
125. R. Singh and D. Patel, "e-Choupal and ICT-based interventions in rural agriculture," 2021.
126. R. Sison, “Team-centered approaches to AI adoption in Philippine organizations: Cultural and leadership factors,” Asia-Pacific Business Review, vol. 22, no. 3, pp. 55–77, 2021.
127. R. Vaidehi, A. B. Reddy, and S. Banerjee, "Explaining Caste-based Digital Divide in India," 2021. [Online]. Available: https://arxiv.org/abs/2106.15917
128. Raja, R., & Nagasubramani, P. C. (2018). Impact of modern technology in education. Journal of Applied and Advanced Research, 3(1), 33–35. https://doi.org/10.21839/jaar.2018.v3i1.165
129. Raman, A., Ramesh, P., & Shenoy, G. (2024). Exploring gendered attitudes toward artificial intelligence in Indian universities. Journal of Educational Research and Practice, 14(1), 34–51.
130. Reserve Bank of India, Financial Inclusion and Digital Banking: The Role of JAM Trinity, 2023.
131. Reserve Bank of India, Financial Inclusion Through JAM Trinity, 2023. [Online]. Available: https://www.rbi.org.in
132. Rest of World, "Caste-Based Divides in the Indian Tech Industry," 2022. [Online]. Available: https://restofworld.org/2022/tech-india-caste-divides
133. Rest of World, Caste-based divides in the Indian tech industry, 2022.
134. Bhatia-Kalluri, “Challenges faced by rural micro-entrepreneurs in e-commerce adoption: A study in India,” International Journal of Rural Management, vol. 17, no. 1, pp. 24–45, 2021.
135. S. Kampa, “Integration of Technology Readiness Index and TAM in m-learning adoption,” Emerald Open Research, 2023. [Online]. Available: https://www.emerald.com/
136. S. Mukherjee, "Digital Inclusion Policies in India: A Critical Assessment," Journal of Information Policy, vol. 12, pp. 123–145, 2022. [Online]. Available: https://www.jstor.org/stable/10.5325/jinfopoli.12.2022.0123.
137. S. Rathore and A. Goyal, "Enhancing AI adoption through real-world application: TAM extended model," 2024. [Online]. Available: https://www.emerald.com/
138. S. Sharma and B. Kapoor, "Technology Adoption and Entrepreneurial Orientation for Rural Women: Evidence from India," Technological Forecasting and Social Change, vol. 160, 2021, Art. no. 120236. [Online]. Available: https://www.researchgate.net/publication/343669911

139. S. Sharma, K. K. Jha, and B. Thangjam, "Digital Transformation in India: Perspectives, Challenges, and Future," Research Journal of Agricultural Sciences, vol. 15, no. 1, pp. 31–37, 2023. [Online]. Available: https://www.researchgate.net/publication/383409687
140. S. Shinde, "90% women view GenAI as crucial for career growth, says Nasscom-BCG report," Business Standard, Aug. 8, 2024. [Online]. Available: https://www.business-standard.com/companies/news/90-women-view-genai-as-crucial-for-career-growth-says-nasscom-bcg-report-124080800935_1.html
141. Santa Clara University Scholar Commons, Digital Initiatives & Scholar Commons, Santa Clara University Library Publications, no. 181, 2021.
142. Sharma, R., & Singh, M. (2021). Challenges in AI integration in Indian education: A review of digital disparities. Journal of Educational Planning and Administration, 35(2), 65–80.
143. Singh, A. (2021). Gendered dimensions of digital transformation in India. Indian Journal of Gender Studies, 28(3), 321–338.
144. Spector, J. M. (2020). Thinking about the future of educational technology. Educational Technology Research and Development, 68, 2079–2095. https://doi.org/10.1007/s11423-020-09807-0
145. Bhattacharya, “Social barriers in digital access: A study of gender and caste dynamics in rural India,” Indian Journal of Technology and Society, vol. 7, no. 2, pp. 120–138, 2022.
146. T. Hill, N. D. Smith, and M. F. Mann, “Role of efficacy expectations in predicting the decision to use advanced technologies: The case of computers,” Journal of Applied Psychology, vol. 72, no. 2, pp. 307–313, 1987.
147. Teo, T. (2011). Factors influencing teachers’ intention to use technology: Model development and test. Computers & Education, 57(4), 2432–2440. https://doi.org/10.1016/j.compedu.2011.06.008
148. The International Review of Research in Open and Distributed Learning, "Exploring the Digital Divide in Open Education," vol. 24, no. 3, 2023.
149. Thomas, A., & Mathew, R. (2023). Digital skill acquisition among Kerala’s women graduates: Aspirations and anxieties. South Asia Journal of Human Resources. https://doi.org/10.1177/232209372311234
150. Time, "India Is Emerging as a Key Player in the Global AI Race," 2024. [Online]. Available: https://time.com/7018294/india-ai-artificial-intelligence-ambani/
151. Time, "India’s AI leadership and the role of government-backed projects like JioBrain," 2024.
152. UNDP, Digital Inclusion in a Dynamic World, 2024. [Online]. Available: https://www.undp.org/sites/g/files/zskgke326/files/2024-05/undp_digital_inclusion_in_a_dynamic_world.pdf
153. UNESCO, Universal Digital Literacy Programs: Lessons for India, 2023b, United Nations Educational, Scientific and Cultural Organization. [Online]. Available: https://www.unesco.org/en/digital-education
154. UNESCO. (2023). AI and education: Guidance for policy-makers. United Nations Educational, Scientific and Cultural Organization. https://unesdoc.unesco.org/ark:/48223/pf0000382280
155. University of Georgia’s Institute for Resilient Infrastructure Systems, Structural Barriers in Technology Adoption among Marginalized Communities, 2023. [Online]. Available: https://iris.uga.edu/research/structural-barriers-technology-adoption
156. H. Vroom, Work and Motivation. New York, NY, USA: Wiley, 1964.
157. Rajam, A. B. Reddy, and S. Banerjee, "Explaining Caste-Based Digital Divide in India," Telematics and Informatics, vol. 65, 2021. [Online]. Available: https://doi.org/10.1016/j.tele.2021.101719
158. V. Raman, P. Mehta, and D. Sinha, "Adoption of ChatGPT and AI tools among Indian university students: A multi-city study," 2024. [Online]. Available: https://www.sciencedirect.com/
159. V. Soundararajan, G. Sharma, and H. Bapuji, "Caste, Social Capital and Precarity of Labour Market Intermediaries: The Case of Dalit Labour Contractors in India," Organization Studies, vol. 44, no. 7, pp. 1053–1075, 2023. [Online]. Available: https://doi.org/10.1177/01708406231175319
160. Varghese, R., & Kumar, J. (2021). Education in the era of AI: Adoption patterns across disciplines in Kerala. Kerala Journal of Higher Education Research, 5(2), 101–120.
161. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926.
162. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540
163. Villanueva, R. (2020). Sample size determination in field research. DLSU Journal of Humanities and Social Sciences, 12(2), 45–56.
164. World Bank, Digital Economy Report: The Role of Technology in Economic Inclusion, World Bank Publications, 2022, p. 112. [Online]. Available: https://www.worldbank.org
165. World Bank, Digital Transformation for Inclusive Development: Bridging the Digital Divide in Developing Economies, 2023, pp. 1–3. [Online]. Available: https://www.worldbank.org/en/topic/digital/overview
166. World Bank. (2023). Digital skills for a resilient future: Youth inclusion in the digital economy. https://www.worldbank.org/en/topic/digitaldevelopment/publication/digital-skills
167. World Economic Forum, Bridging the Digital Divide to Accelerate Development, 2022. [Online]. Available: https://www.weforum.org/stories/2022/11/bridging-the-digital-divide-to-accelerate-development
168. World Economic Forum, The Future of Jobs Report 2021, Geneva, WEF, 2021. [Online]. Available: https://www.weforum.org/press/2016/01/100-trillion-by-2025-the-digital-dividend-for-society-and-business/

169. World Economic Forum. (2020). The future of jobs report 2020. https://www.weforum.org/reports/the-future-of-jobs-report-2020
170. World Economic Forum. (2023). Jobs of tomorrow: Large language models and jobs. https://www.weforum.org/reports/jobs-of-tomorrow-large-language-models-and-jobs
171. Zheng and Y. Li, "Gender and technology adoption: A review of the literature," Technology Analysis & Strategic Management, vol. 33, no. 6, pp. 664–682, 2021. [Online]. Available: https://doi.org/10.1080/09537325.2020.1823478
172. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? International Journal of Educational Technology in Higher Education, 16(1), 1–27. https://doi.org/10.1186/s41239-019-0171-0